Machine Learning

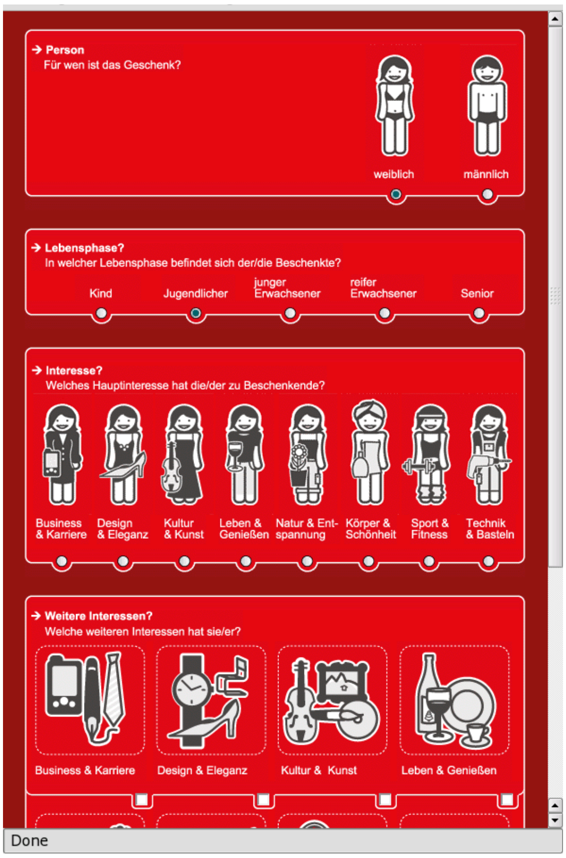
Lars Schmidt-Thieme

Information Systems and Machine Learning Lab (ISMLL)
Institute for Business Economics and Information Systems
& Institute for Computer Science
University of Hildesheim
http://www.ismll.uni-hildesheim.de

What is Machine Learning?

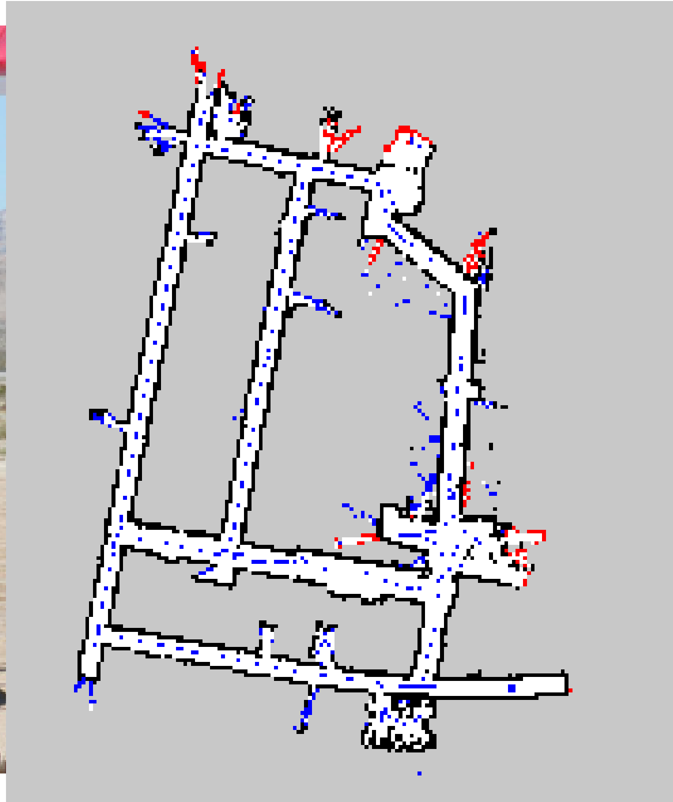
What is Machine Learning?

1. Information Systems: predict what customers will buy.



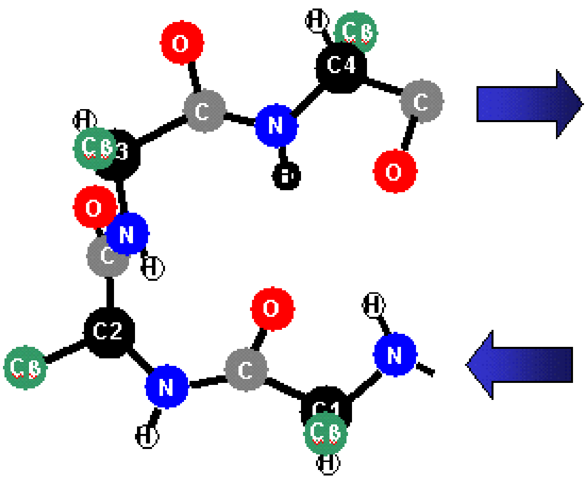
What is Machine Learning?

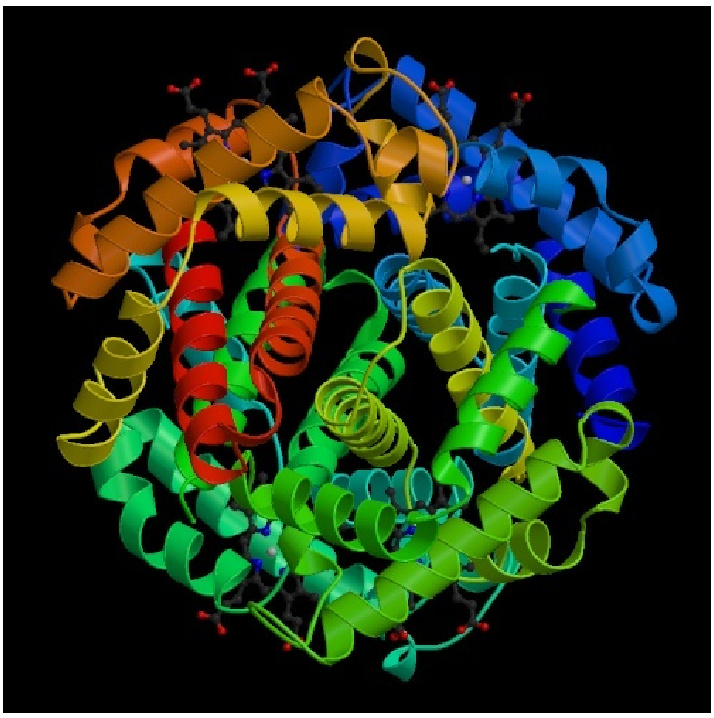
2. Robotics: Build a map of the environment based on sensor signals.



What is Machine Learning?

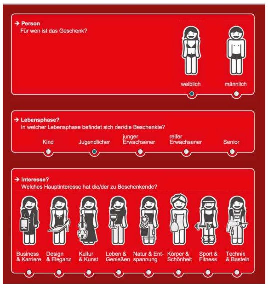
3. Bioinformatics: predict the 3d structure of a molecule based on its sequence.





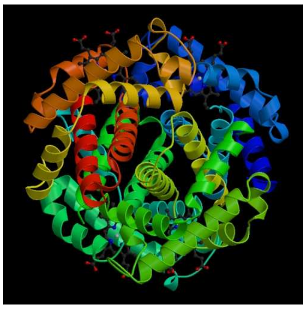
What is Machine Learning?

Information Systems



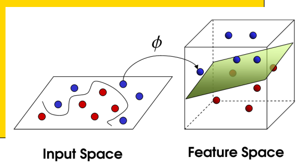
Robotics

Bioinformatics



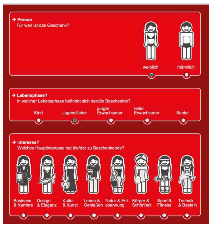
Many Further Applications!

MACHINE LEARNING



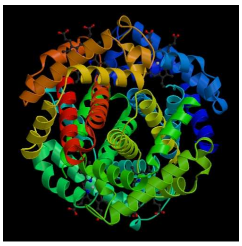
What is Machine Learning?

Information Systems



Robotics

Bioinformatics



Many Further Applications!

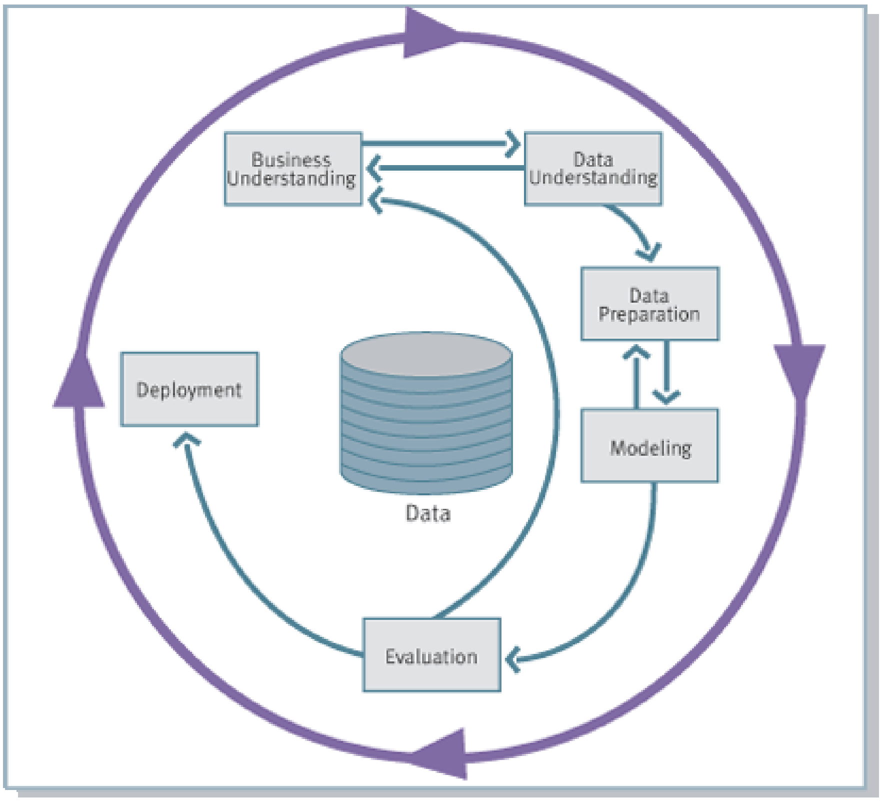
MACHINE LEARNING

OPTIMIZATION

NUMERICS

ALGORITHMICS

Process models



Cross Industry Standard Process for Data Mining (CRISP-DM)

One area of research, many names (and aspects)

machine learning
: historically, stresses learning logical or rule-based models (vs. probabilistic models).

data mining
: stresses the aspect of large datasets and complicated tasks.

knowledge discovery in databases (KDD)
: stresses the embedding of machine learning tasks in applications, i.e., preprocessing & deployment; data mining is considered the core process step.

data analysis
: historically, stresses multivariate regression methods and many unsupervised tasks.

pattern recognition
: name prefered by engineers, stresses cognitive applications such as image and speech analysis.

applied statistics
: stresses underlying statistical models, testing and methodical rigor.

1. **What is Machine Learning?**
2. **Overview**
3. **Organizational stuff**

Machine Learning Problems

1. Density Estimation
2. Regression / Supervised Learning
3. Classification / Supervised Learning
4. Optimal Control / Reinforcement Learning
5. Clustering / Unsupervised Learning
6. Dimensionality reduction
7. Association Analysis

1. Density Estimation

Example 1: duration and waiting times for erruptions of the “Old Faithful” geyser in Yellowstone National Park, Wyoming (Azzalini and Bowman 1990).

continuous measurement from August 1 to August 15, 1985:

- duration (in min.),
- waiting time (in min.)

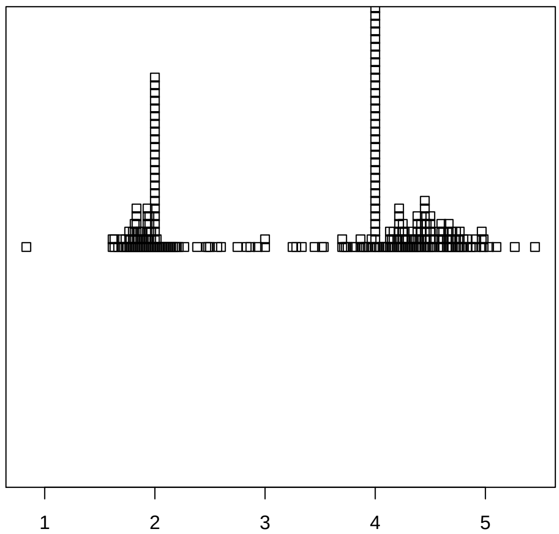
duration:

4.016667, 2.15, 4.0, 4.0, 4.0, 2.0, 4.383333, 4.283333, 2.033333, 4.833333, . . .

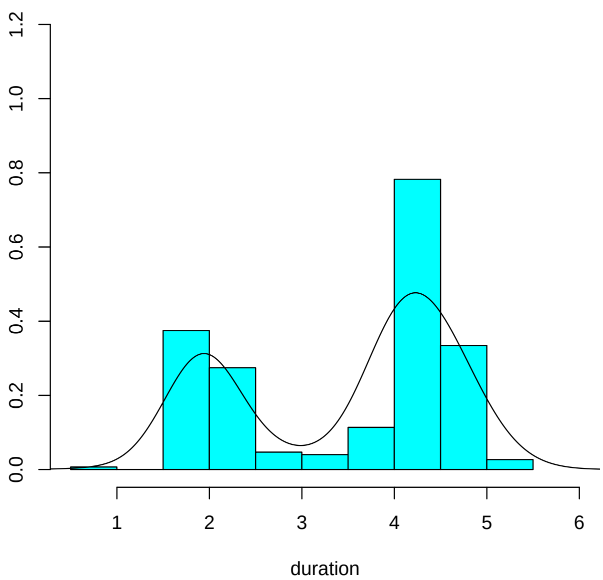
What is a typical duration? waiting time?

1. Density Estimation

durations: 4.016667, 2.15, 4.0, 4.0, 4.0, 2.0, 4.383333, 4.283333, . . .

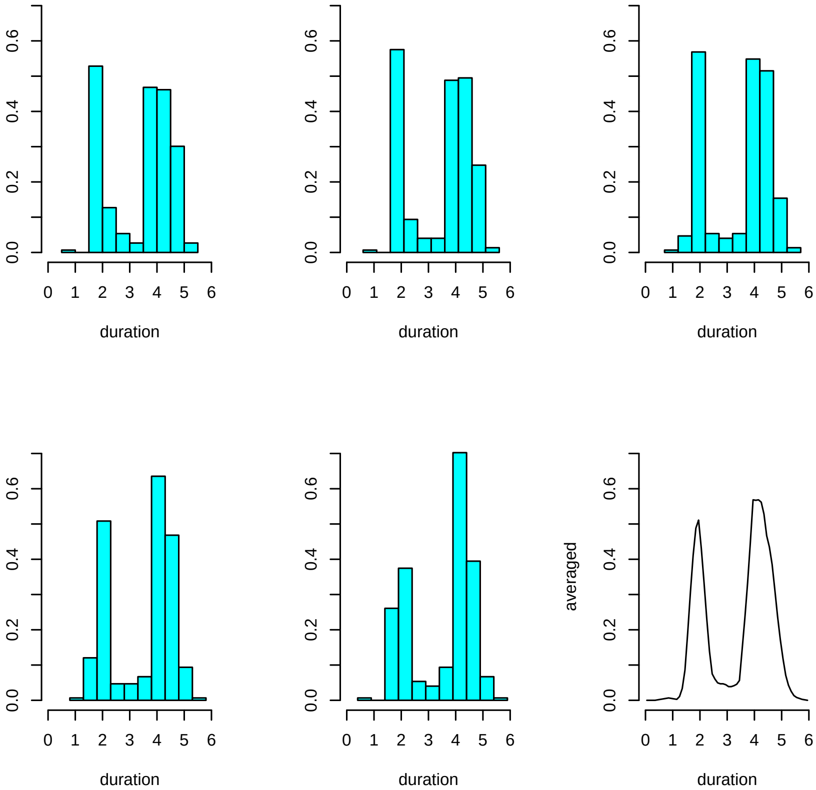


strip chart

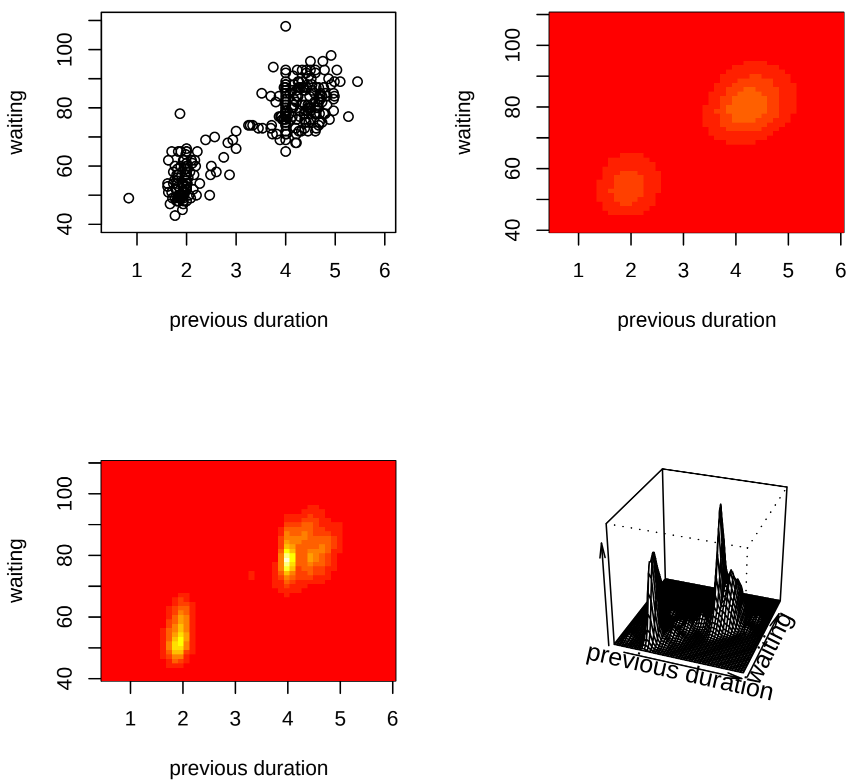


histogram

1. Density Estimation

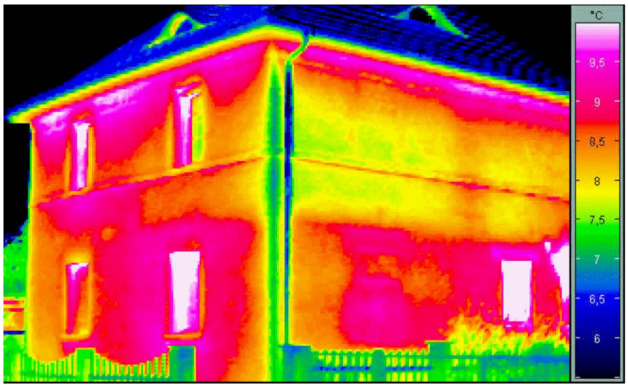


1. Density Estimation



2. Regression

Example 2: how does gas consumption depend on external temperature? (Whiteside, 1960s).



weekly measurements of

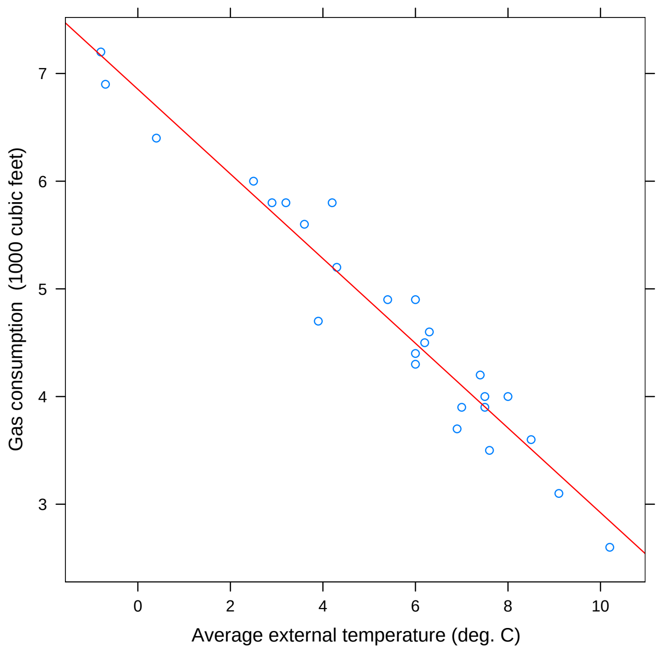
- average external temperature
- total gas consumption
  (in 1000 cubic feets)

A third variable encodes two heating seasons, before and after wall insulation.

How does gas consumption depend on external temperature?

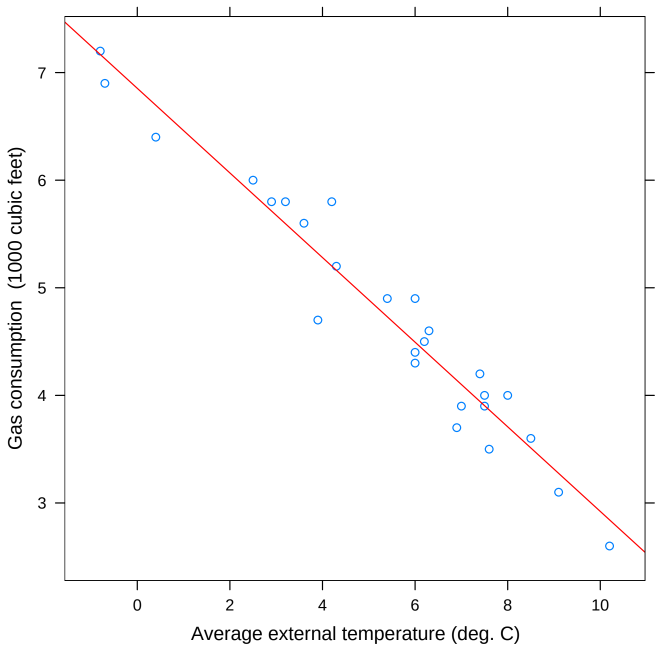
How much gas is needed for a given termperature ?

2. Regression

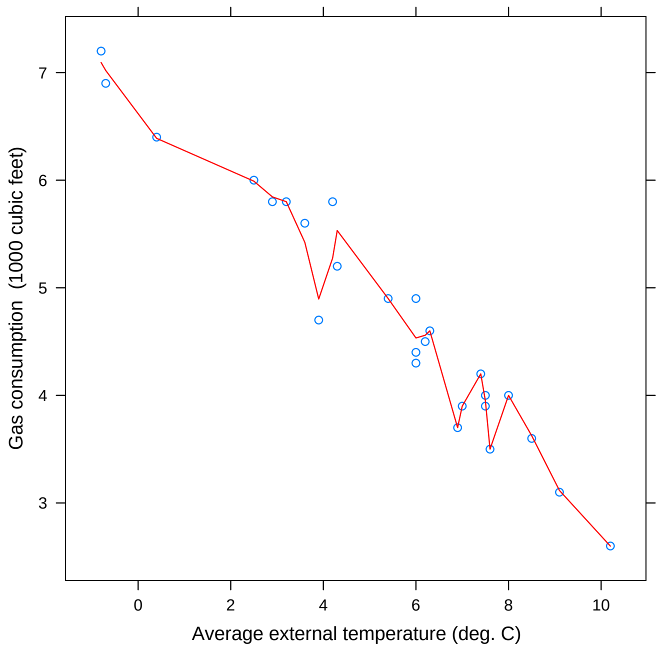


linear model

2. Regression



linear model



more flexible model

3. Classification / Supervised Learning

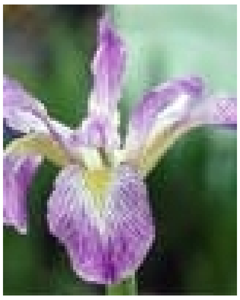
Example 3: classifying iris plants (Anderson 1935).

150 iris plants (50 of each species):

- species: setosa, versicolor, virginica
- length and width of sepals (in cm)
- length and width of petals (in cm)

iris setosa

iris versicolor



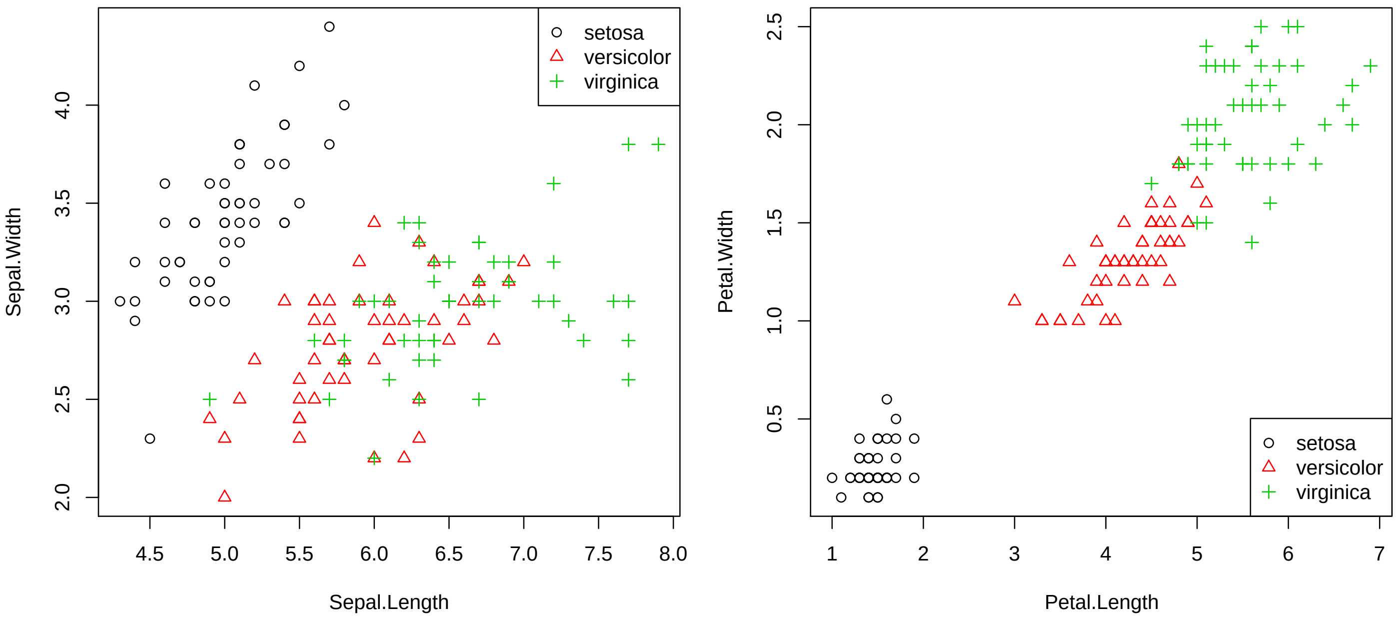
iris virginica

See iris species database (http://www.badbear.com/signa).

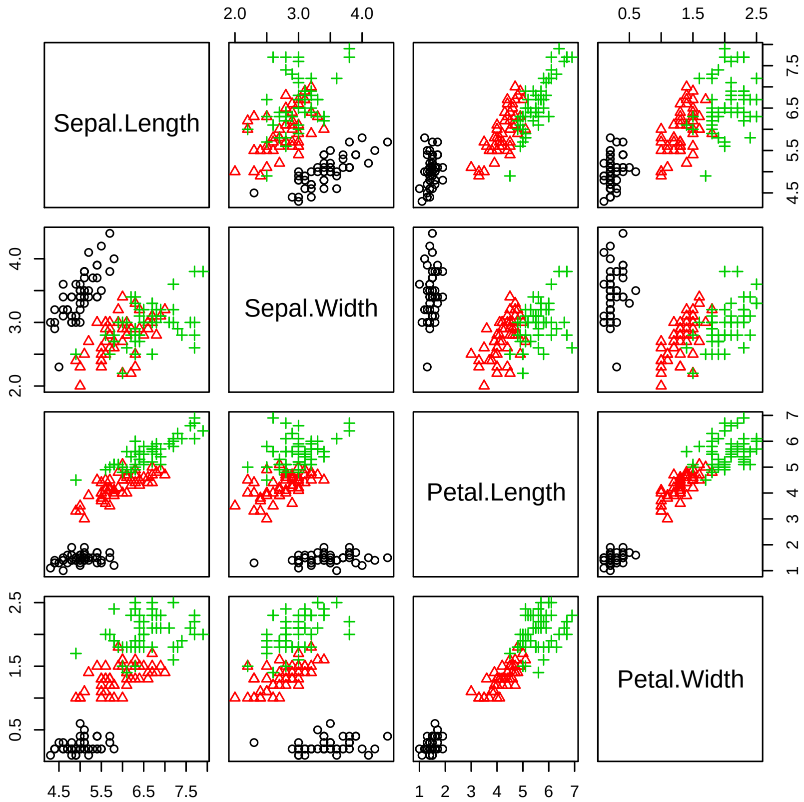
3. Classification / Supervised Learning

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
1	5.10	3.50	1.40	0.20	setosa
2	4.90	3.00	1.40	0.20	setosa
3	4.70	3.20	1.30	0.20	setosa
4	4.60	3.10	1.50	0.20	setosa
5	5.00	3.60	1.40	0.20	setosa
⋮	⋮	⋮	⋮	⋮	
51	7.00	3.20	4.70	1.40	versicolor
52	6.40	3.20	4.50	1.50	versicolor
53	6.90	3.10	4.90	1.50	versicolor
54	5.50	2.30	4.00	1.30	versicolor
⋮	⋮	⋮	⋮	⋮	
101	6.30	3.30	6.00	2.50	virginica
102	5.80	2.70	5.10	1.90	virginica
103	7.10	3.00	5.90	2.10	virginica
104	6.30	2.90	5.60	1.80	virginica
105	6.50	3.00	5.80	2.20	virginica
⋮	⋮	⋮	⋮	⋮	
150	5.90	3.00	5.10	1.80	virginica

3. Classification / Supervised Learning



3. Classification / Supervised Learning



3. Classification / Supervised Learning

Example 4: classifying email (lingspam corpus)

Subject: query: melcuk (melchuk)

does anybody know a working email (or other) address for igor melcuk (melchuk) ?

legitimate email (“ham”)

Subject: ‘

hello ! come see our naughty little city made especially for adults http://208.26.207.98/freeweek/ enter.html once you get here, you won’t want to leave !

spam

How to classify email messages as spam or ham?

3. Classification / Supervised Learning

Subject: query: melcuk (melchuk)

does anybody know a working email (or other) address for igor melcuk (melchuk) ?

$$\Rightarrow \begin{pmatrix} \text{a} & 1 \\ \text{address} & 1 \\ \text{anybody} & 1 \\ \text{does} & 1 \\ \text{email} & 1 \\ \text{for} & 1 \\ \text{igor} & 1 \\ \text{know} & 1 \\ \text{melcuk} & 2 \\ \text{melchuk} & 2 \\ \text{or} & 1 \\ \text{other} & 1 \\ \text{query} & 1 \\ \text{working} & 1 \end{pmatrix}$$

3. Classification / Supervised Learning

lingspam corpus:

- email messages from a linguistics mailing list.
- 2414 ham messages.
- 481 spam messages.
- 54742 different words.
- an example for an early, but very small spam corpus.

3. Classification / Supervised Learning

All words that occur at least in each second spam or ham message on average (counting multiplicities):

	!	your	will	we	all	mail	from	do	our	email
spam	14.18	7.45	4.36	3.42	2.88	2.77	2.69	2.66	2.46	2.24
ham	0.38	0.46	1.93	0.94	0.83	0.79	1.60	0.57	0.30	0.39

	out	report	order	as	free	language	university
spam	2.19	2.14	2.09	2.07	2.04	0.04	0.05
ham	0.34	0.05	0.27	2.38	0.97	2.67	2.61

example rule:

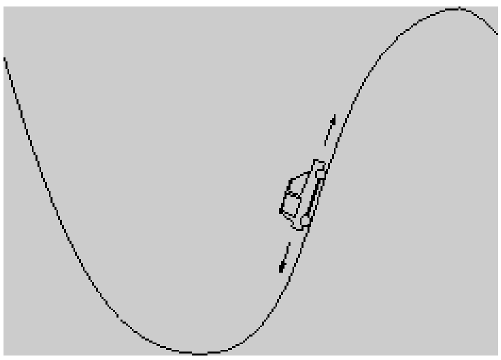
if freq("!")$\geq$ 7 and freq("language")=0 and freq("university")=0 then spam,
else ham

Should we better normalize for message length?

4. Reinforcement Learning

A class of learning problems where the correct / optimal action never is shown, but only positive or negative feedback for an action actually taken is given.

Example 5: steering the mountain car.



Observed are

- x-position of the car,
- velocity of the car

Possible actions are

- accelerate left,
- accelerate right,
- do nothing

The goal is to steer the car on top of the right hill.

4. Reinforcement Learning / TD-Gammon

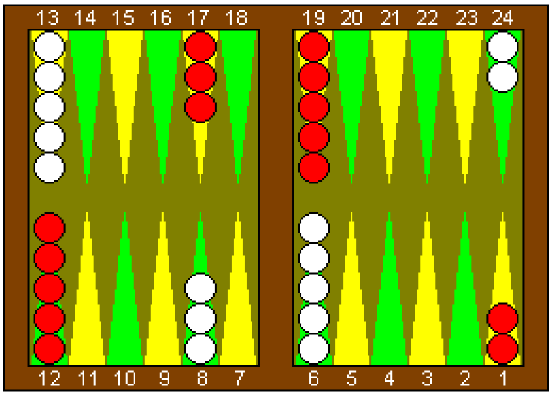


Figure 2. An illustration of the normal opening position in backgammon. TD-Gammon has sparked a near-universal conversion in the way experts play certain opening rolls. For example, with an opening roll of 4-1, most players have now switched from the traditional move of 13-9, 6-5, to TD-Gammon's preference, 13-9, 24-23. TD-Gammon's analysis is given in Table 2.

Program	Hidden Units	Training Games	Opponents	Results
TD-Gam 0.0	40	300,000	Other Programs	Tied for Best
TD-Gam 1.0	80	300,000	Robertie, Magriel, ...	−13 pts / 51 games
TD-Gam 2.0	40	800,000	Var. Grandmasters	−7 pts / 38 games
TD-Gam 2.1	80	1,500,000	Robertie	−1 pts / 40 games
TD-Gam 3.0	80	1,500,000	Kazaros	+6 pts / 20 games

5. Cluster Analysis

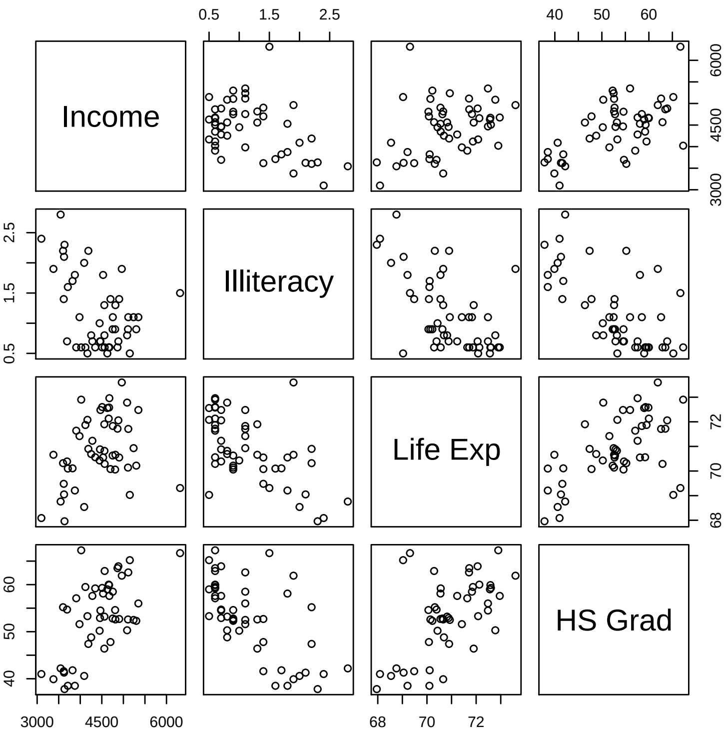
Finding groups of similar objects.

Example 6: sociographic data of the 50 US states in 1977.

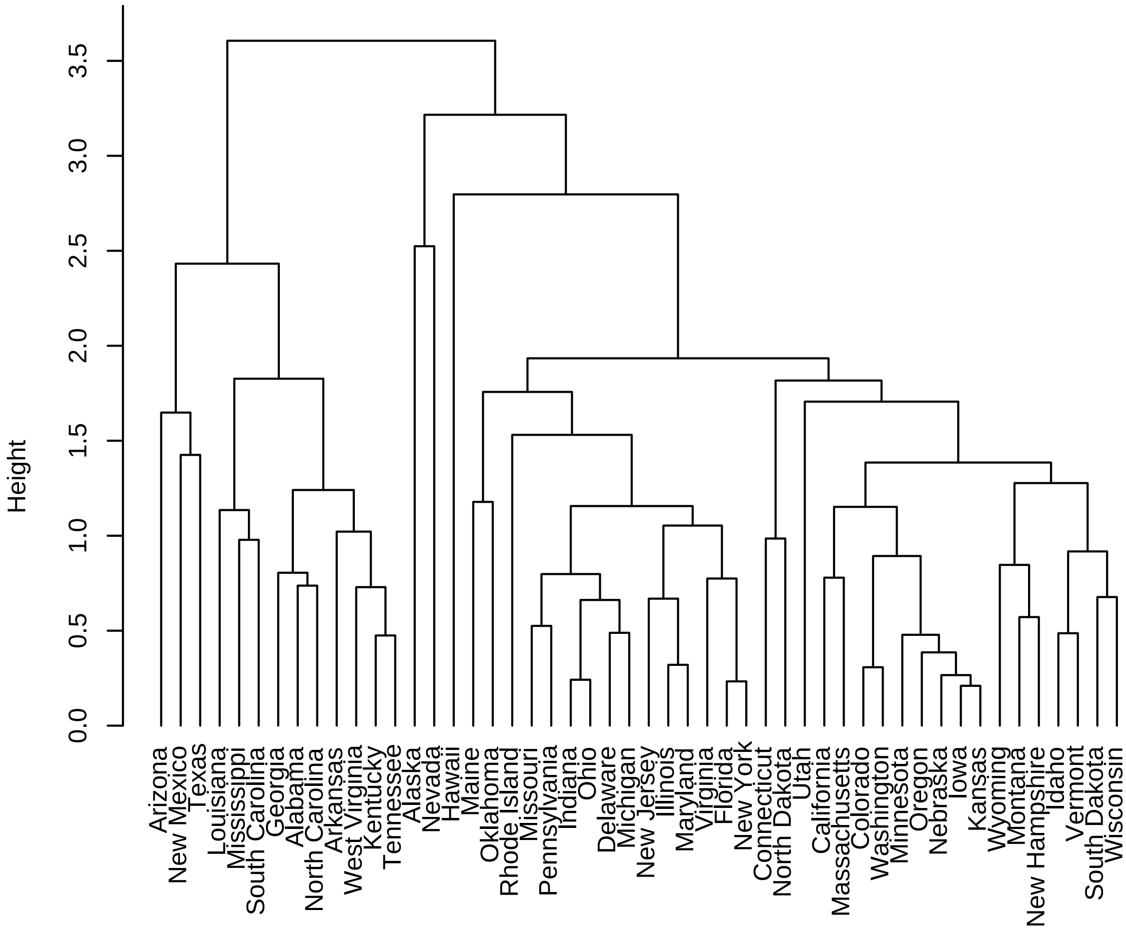
state dataset:

- income (per capita, 1974),
- illiteracy (percent of population, 1970),
- life expectancy (in years, 1969–71),
- percent high-school graduates (1970).

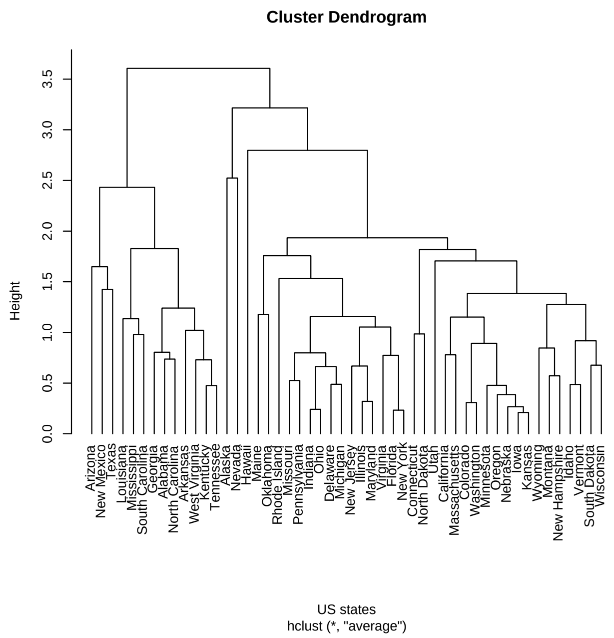
and some others not used here.

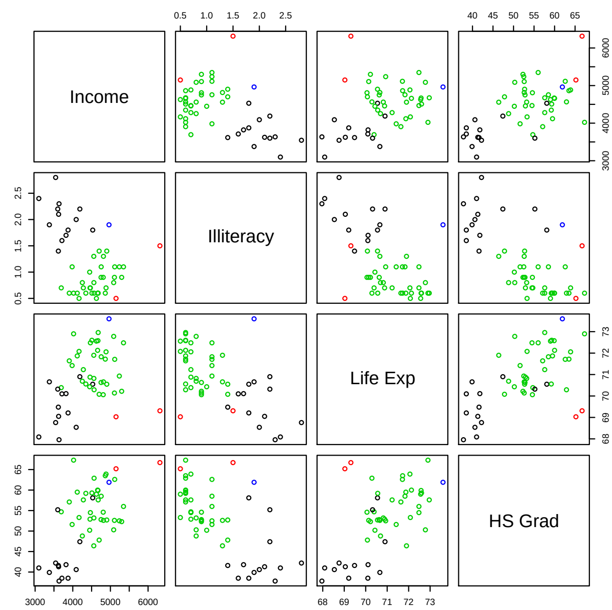


5. Cluster Analysis



5. Cluster Analysis





black: Arizona et al., red: Alaska & Nevada, green: Californa et al., blue: Hawaii.

7. Association Analysis

Association rules in large transaction datasets:

- look for products frequently bought together (**frequent itemsets**).

- look for rules in buying behavior (**association rules**)

Examples:

- $\{\text{beer}, \text{pampers}, \text{pizza}\}$ (support=0.5)
  $\{\text{bread}, \text{milk}\}$ (support=0.5)

- If beer and pampers, then pizza (confidence= 0.75)
  If bread, then milk (confidence=0.75)

cid	beer	bread	icecream	milk	pampers	pizza
1	+	−	−	+	+	+
2	+	+	−	−	+	+
3	+	−	+	−	+	+
4	−	+	−	+	−	+
5	−	+	+	+	−	−
6	+	+	−	+	+	−

1. **What is Machine Learning?**

2. **Overview**

3. **Organizational stuff**

Exercises and tutorials

- There will be a weekly sheet with two exercises handed out **each Thursday** in the lecture.
  1st sheet will be handed out this Thur. 25.10.
- Solutions to the exercises can be submitted until **next Wednesday noon**
  1st sheet is due Mon. 6.11. 1pm
- Mode of corrections is still to be decided on until next lecture.
- Tutorials **each Thursday 11–12** instead of the lecture, 1st tutorial at Thur. 25.10.
- Successfull participation in the tutorial gives up to 10% bonus points for the exam.

Exam and credit points

- There will be a written exam at end of term (2h, 4 problems).
- The course gives 7 ECTS (3+1 SWS).
- The course can be used in the modules
  - WI BSc. / CS Area Artificial Intelligence and Machine Learning,
  - IMIT BSc. / IT3-E Machine Learning,
  - IMIT BSc. / BW2-BI Business Intelligence,
  - IMIT MSc. / IT Machine Learning, *or*
  - IMIT MSc. / BW Business Intelligence.

Some books

- Richard O. Duda, Peter E. Hart, David G. Stork (2001):
  Pattern Classification, Springer.

- Trevor Hastie, Robert Tibshirani, Jerome Friedman (2001):
  The Elements of Statistical Learning, Springer.

- W. N. Venables, B. D. Ripley (2002):
  Modern Applied Statistics with R, Springer.

- Tom Mitchell (1997):
  Machine Learning, McGraw-Hill.

- Christopher M. Bishop (1996):
  Neural Networks for Pattern Recognition, Oxford University Press.

Some First Machine Learning / Data Mining Software

- R (v2.6.0, 3.10.2007; http://www.r-project.org).

- Weka (v3.4.11, 31.5.2007; http://www.cs.waikato.ac.nz/ ml/).

- SAS Enterprise Miner (commercially).

Public data sets:

- UCI Machine Learning Repository
  (http://www.ics.uci.edu/ mlearn/)

- UCI Knowledge Discovery in Databases Archive
  (http://kdd.ics.uci.edu/)

Persons

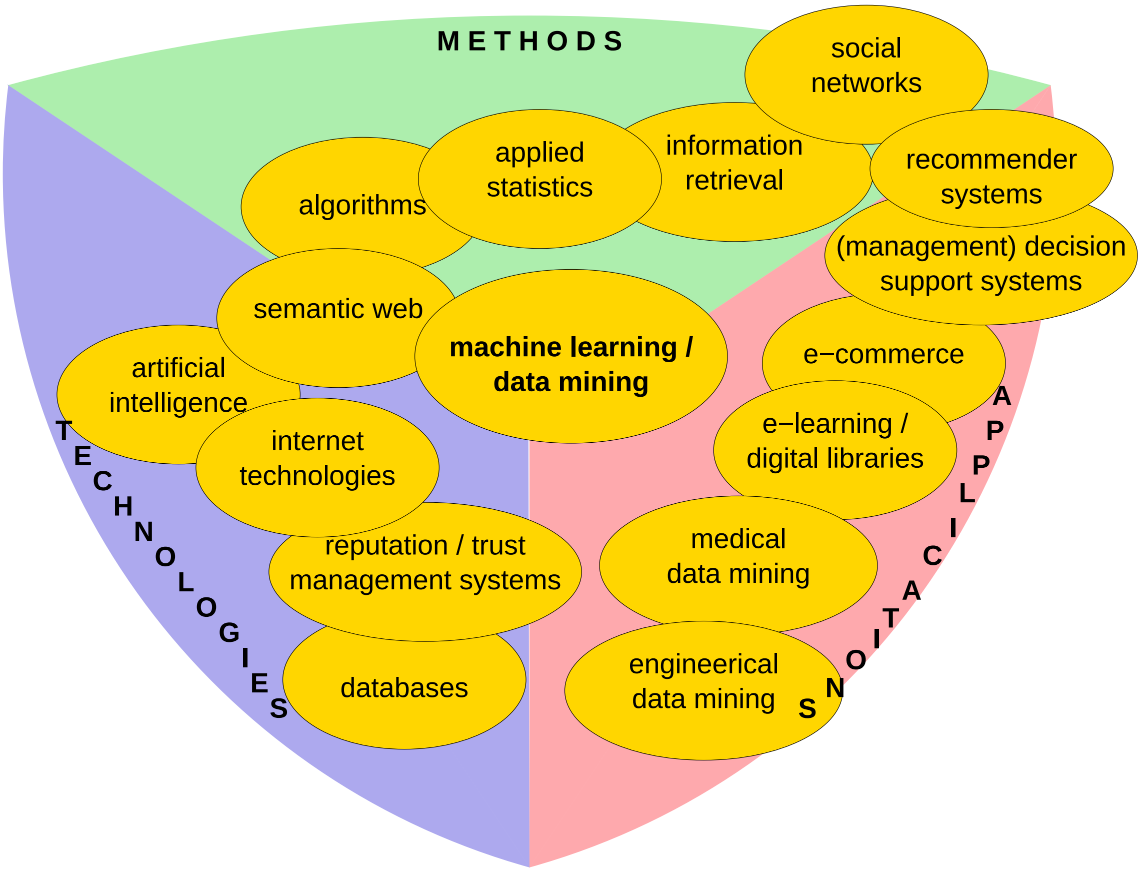
Lars Schmidt-Thieme

Krizstian Buza
Zeno Gantner
Artus Krohn-Grimberghe
Leandro Marinho
Christine Preisach
Steffen Rendle
Karen Tso
— research assistants

Kerstin Hinze-Melching
— secretary
Jörg Striewski
— technician

Andrè Busche
Benedikt Nienhaus
Christina Roland
— Student Research Assistants

Research Areas



Master Seminar on Fraud Detection

Wednesday, 16-18, C213 Spl

- Systems that automatically detect fraudulent user behavior.
- Introduction of Seminar on **Wed. 24.10., 16-18, C213 Spl**.
- More information can be found at
  http://www.ismll.uni-hildesheim.de/lehre/fd-07w/index.html